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Price transmission in biofuel-related global agricultural networks

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Abstract: This article investigates the connections among the prices of biofuels, agricultural commodities and other relevant assets in Europe, the US, and Brazil. The analysis includes a comprehensive data set covering price data for 38 traded titles during the period from 2003 to 2020. We used the minimum spanning tree (MST) approach to identify price connections in a complex trading system. Our analysis of mutual price connections reveals the major defining features of world-leading biofuel markets. We provide the characteristics of the main bioethanol and biodiesel markets with respect to government policies and technical and local features of the production and consumption of particular biofuels. Despite a relatively long and dynamically evolving history of biofuels, the biofuel systems in the US, Brazil and Europe do not converge toward the same pattern of relations among fossil fuels, biofuels, agricultural commodities and financial assets.

Keywords: biodiesel; energy and agricultural policies; ethanol; minimum spanning tree

As identified in the early contributions of Tyner and Taheripour (2008) and Tyner (2010), agricultural and energy markets had not been closely correlated before the advent of biofuels. All this has changed during the last 20 years (Timilsina 2018).

The goal of this article is to take empirical data on agricultural and energy commodities and to evaluate their co-movement from a dynamic perspective. We provide an empirical analysis of a global system of biofuel-induced price transmission among the main energy and agricultural commodities and potentially related financial assets. Our results show a dynamic evolution of the biofuel-related price co-movements with different levels of price integration during the four main sub-periods identified in our analysis. Despite a relatively long and dynamically evolving history of biofuels, the biofuel systems in the US, Brazil and Europe do not converge toward the same pattern of relations among fossil fuels, biofuels, agricultural commodities and financial assets.

As outlined in the comprehensive book on biofuel policies by de Gorter et al. (2015), the literature on fuel *versus* food economic policies and resulting price linkages uses three main modelling approaches – theoretical models of channels leading to price con-

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nectedness (Ciaian and Kancs 2011a, b; Rajčaniová et al. 2013, 2014; Drabík et al. 2014, 2015, 2016; Bouteijn et al. 2017), partial and general equilibrium models simulating market interdependencies (Beckman et al. 2012; Campbell et al. 2018; Taheripour et al. 2021; Zhao et al. 2021), and time series analyses, which is a method used in this article.

Mutual co-movement of time series of prices of biofuels and related assets is a subject of a large body of literature which was reviewed in detail by Serra (2013) and more recently by Janda and Kristoufek (2019). A large number of different time series techniques have already been used for the investigation of biofuel-related price transmission analyses. Some of them are very standard mainstream time series econometrics techniques, such as the vector error correction model (Zhang et al. 2010; Ciaian and Kancs 2011a, b; Rajčaniová and Pokrivčák 2011), vector autoregression or structural vector autoregression (Capitani et al. 2018; Dalheimer et al. 2021), generalised autoregressive conditional heteroscedasticity models (Abdelradi and Serra 2015), autoregressive distributed lag (Dutta 2018) and more general Granger causality approaches (Bastianin et al. 2016). However, less common techniques, such as copulas (Reboredo 2012; Tiwari et al. 2021), wavelets (Pal and Mitra 2017) and frequency-dependent spillovers (Pal and Mitra 2020), are used as well.

In this article, we use the minimum spanning tree (MST) technique which was introduced to biofuel-related research by Krištoufek et al. (2012) and Lautier and Raynaud (2012). In large systems of variables, it is especially difficult to identify connections above the standard pairwise perspective, as the testing statistics or estimated parameters are, by definition, given for a specific one-to-one relationship. MSTs are built on such pairwise connections as well, but they provide a more complex picture of the connections, as the co-movement dynamics are represented as a connected graph. This type of visualisation leads to a better understanding of the interconnections in the whole system together rather than studying the connections separately, so it makes the interpretation much more straightforward.

Compared with investigators in earlier articles dealing with MSTs in biofuel-related networks (Krištoufek et al. 2012; Lautier and Raynaud 2012), we have used a wider set of potentially relevant commodities and a longer period of analysis. Therefore, our main contribution to the biofuel-related MSTs literature is data-based, and we also provide improved, colour-based visualisation of the MSTs.

MATERIAL AND METHODS

We investigated the co-movement of biofuel-related prices through MSTs. The starting points of MST analyses are the Pearson pairwise correlation coefficients, ρ_{ij}, which were used in the seminal agenda-setting articles by Tyner and Taheripour (2008) and Tyner (2010) to illustrate the paradigm of integrated energy and agricultural markets. The MSTs reconstruct the correlation structure from the correlation matrix through distances and the resulting tree-like structure that represents the most important connections in a system of variables or a network. To translate the correlations of ρ_{ij} between variables i and j into distances, we followed the method of Mantegna (1999) by transforming the Pearson correlation coefficients of ρ_{ij} so that they represented an appropriate measure of distance by using the following formula:

$$d_{ij} = \sqrt{2\left(1 - \rho_{ij}\right)} \quad (1)$$

where: d_{ij} – distance; ρ_{ij} – Pearson pairwise correlation coefficient.

Matrix $\mathbb{D}$, composed of the distances d_{ij}, meets all the criteria of the Euclidean metric.

The values of the coefficients d_{ij} are strictly positive, varying between 0 and 2. For $d_{ij} = 0$, we have the perfect positive correlation, $d_{ij} = \sqrt{2}$, which means no correlation, and $d_{ij} = 2$ represents the perfect negative correlation. This transformation is not strictly required for the purpose of this article, which is the creation of a cluster structure of closely related commodities. However, we have used it to be consistent and comparable with the mathematical graph theory literature, in which it is considered important to use distance metrics (i.e. using non-negative distances).

There are several algorithms that can be used to find the MST. In our analysis, we used Kruskal's algorithm (Kruskal 1956). The basic way that this algorithm works is that it starts with all of the possible $n(n-1)/2$ connections (where: n – number of variables) and subsequently systematically eliminates the weakest links, or in our case, the largest distances between the nodes, until it is still possible to connect all nodes with their links. This elimination results in a significantly lower number of linkages that are now decreased to only the $n-1$ value for the MST. Such a simplified graph is much more legible and easier to comprehend visually than is the initial matrix of all pairwise correlation coefficients. All of the computations necessary for this part were processed

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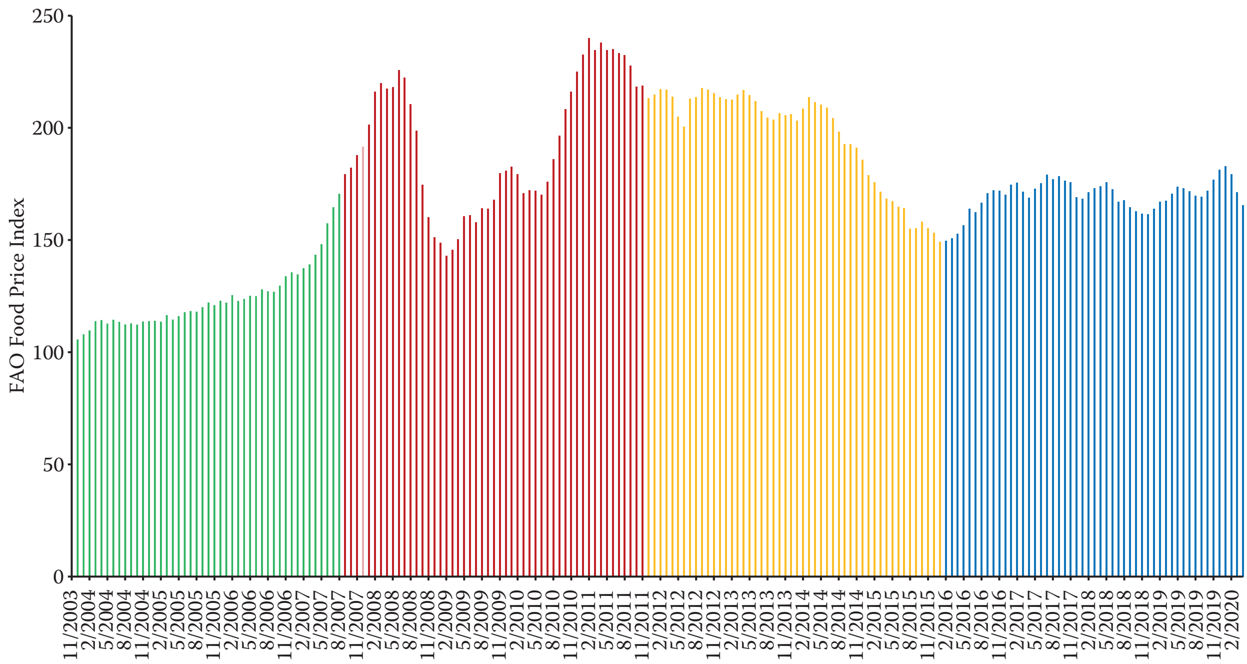

Figure 1. FAO Food Price Index

The years 2002–2004 represent 100 (the base period); the colours serve to distinguish 4 time periods
Source: Own calculations based on FAO (2020)

in R software (version 3.4.4), and the MSTs were visualised through the igraph package (version 1.2.5).

The problem that we would likely have to face when it comes to using MST analysis lies in the possible temporal instability of the links between each of the inputs. As shown by Krištoufek et al. (2012), the structure of the MST on the basis of monthly or weekly data may be different, so although we are using the economically most natural weekly data, we must be concerned with what happens if we consider different data frequencies. Therefore, to check the stability of the links and find out whether they are actually relevant or appear in the chosen structure with weekly time-frequency rather randomly, we used the bootstrapping technique, which was introduced by Tumminello et al. (2007). To do so, we took the already created MST and constructed a bootstrapped version of the time series from which the previous MST was created and on which it was based. We then kept the whole data set as it was; however, we then allowed for the data set to be randomly reorganised, and we also allowed repetitions, which can simply mean that some links will be completely omitted and some can appear multiple times. This will create a new MST structure, whose links are then recorded, while this process is repeated 1 000 times overall. The procedure finally left us with a precise number of how many times out of 1 000, a certain link appeared in our MST construction. All of these values were then marked for each edge as $b_{ij} \in [0; 1]$, which is the ratio of the actual number of appearances in the MST to the total number of realised bootstraps. We considered a value greater than 0.5 as a fairly stable link.

Our data set contains 38 price time series of different commodities and assets that are in some way possibly connected to the prices of biofuels. We considered the following: Brazilian and US ethanol, European Union and US biodiesel, Brazilian sugar, corn, sugar beets, sugar cane, wheat, palm oil, rapeseed, soybeans, sunflower seeds, cattle, cocoa, coffee, cotton, orange juice and rice, Brazilian, US and German diesel and gasoline, Brent crude, heating oil, West Texas Intermediate (WTI) oil, exchange rates [Brazilian real (BRL)/USD, USD/EUR] and indexes [Bovespa, German stock index (DAX), Dow Jones, Financial Times Stock Exchange (FTSE) 100, Standard and Poor's (S&P) 500, Federal Funds Effective Rate, London Interbank Offered Rate (LIBOR)]. A detailed description of the data is provided in Schererová (2020).

For our analysis, we transformed our raw data into logarithmic returns according to this formula:

$$r_t = \log\left(P_t\right) - \log\left(P_{t-1}\right) = \log\frac{P_t}{P_{t-1}} \tag{2}$$

where: r_t – logarithmic return; P_t – prices.

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For the construction of MSTs, we needed to produce a correlation matrix first, which meant that such correlations needed to be defined. The studied series thus could not contain unit roots. A combination of the augmented Dickey-Fuller test (Dickey and Fuller 1979) and the Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al. 1992) allowed the log-return series to be used for the analysis.

Each of our time series was a collection of weekly prices from the period from 21 November 2003 until 24 April 2020. As far as the day of the collection was concerned, we always looked for Friday data; only when Friday data were not available did we use the data from the closest previous day. The span that our data set covers is approximately 18 years, which leads to 859 weekly observations.

As shown in Figure 1, we divided the whole data set into smaller parts according to the price fluctuations captured by the Food Price Index, which is published by the FAO (2020). These periods are as follows:

– Period I: 21. 11. 2003 – 31. 08. 2007 (199 observations)
– Period II: 07. 09. 2007 – 28. 10. 2011 (217 observations)
– Period III: 4. 11. 2011 – 25. 12. 2015 (217 observations)
– Period IV: 01. 01. 2016 – 24. 04. 2020 (226 observations)

RESULTS AND DISCUSSION

In the MST graphs, each edge that connects two assets has two numerical values depicted next to it. First, the one without brackets represents the distance d_{ij} that denotes the strength of the correlation between the two assets. In this case, all distances d_{ij} vary from 0 to $\sqrt{2}$, where smaller numbers represent a stronger relationship between the two (as it is a distance). An important feature of our data is that in all of the MST graphs, we have only non-negative correlations. The MST algorithm, which minimises distances in the whole graph, is focused on positively correlated pairs of assets. As long as there are enough positively correlated pairs of assets, the negatively correlated pairs of assets are not included in the MSTs, which is the case in this article.

The second important number depicted in the MST graphs, the one within brackets, represents the value created by the bootstrap, b_{ij}, representing the ratio between the number of times that this particular pairwise link appeared in the bootstrapped MST from the 1 000 repetitions. We used the value of $b_{ij} = 0.5$ as a value from which to consider certain links as being stable.

Looking at the MST for the entire period (Figure 2), we describe how the previously defined methodology works. The first pair that is created with the lowest number, representing the closest link or the strongest relationship, is the Dow Jones and the S&P 500, with the distance of 0.223, which creates a pair in all of the MSTs. This finding is quite intuitive, considering that they are both from the US stock market. We can also say with confidence that all financial indexes are interconnected to some extent and that they will form a cluster in every period of our analysis. In the second step of the construction of this MST, Brent crude oil and WTI are connected with the distance of 0.498, along with a strong connection of Brent crude oil with heating oil as well (0.556).

The construction of the MST was not continuous in the sense that we would obtain an initial continuous graph which would simply be enlarged in any new step. Instead, as highlighted by our example of the first pair of stock indexes and the second pair of fossil fuels, we first created several (possibly non-connected) clusters, which were connected only in the subsequent steps of the MST's creation. This method, in particular, means that we should not expect any linearity (monotonicity) in the constructed MST. For example, in Figure 2, we have a link of US gasoline, US diesel, Brazilian diesel and Brazilian gasoline in which the links between country-specific fossil fuels were created during the early steps of MST construction; therefore, they have low distances (approximately 0.6 for US fuels and 0.7 for Brazilian fuels). However, the connection of country-specific fuel clusters in a global fossil fuel cluster was done in later steps, as documented by a much higher distance between US diesel and Brazilian diesel ($d = 1.269$).

We stress that all of these links, along with other important relationships that were formed, are not random and that their bootstrap value (in the brackets) is usually equal to 1 or is very close to 1, meaning that these connections appeared in all or almost all of the 1 000 bootstrapped cases. This finding ensures that these relationships are stable throughout the whole period and will appear in nearly every MST that we analyse. Another important connection is that between the two indexes FTSE 100 and DAX, both coming from the European financial markets. The algorithm proceeded with the elimination of the weakest connections, leaving us with the previously mentioned $n-1$ connections (edges), which in this case represent the 37 edges that can be observed in the MST structure. What resulted from such elimination were various clusters, which were formed into groups – clusters based on certain similarities that the assets possess, as further

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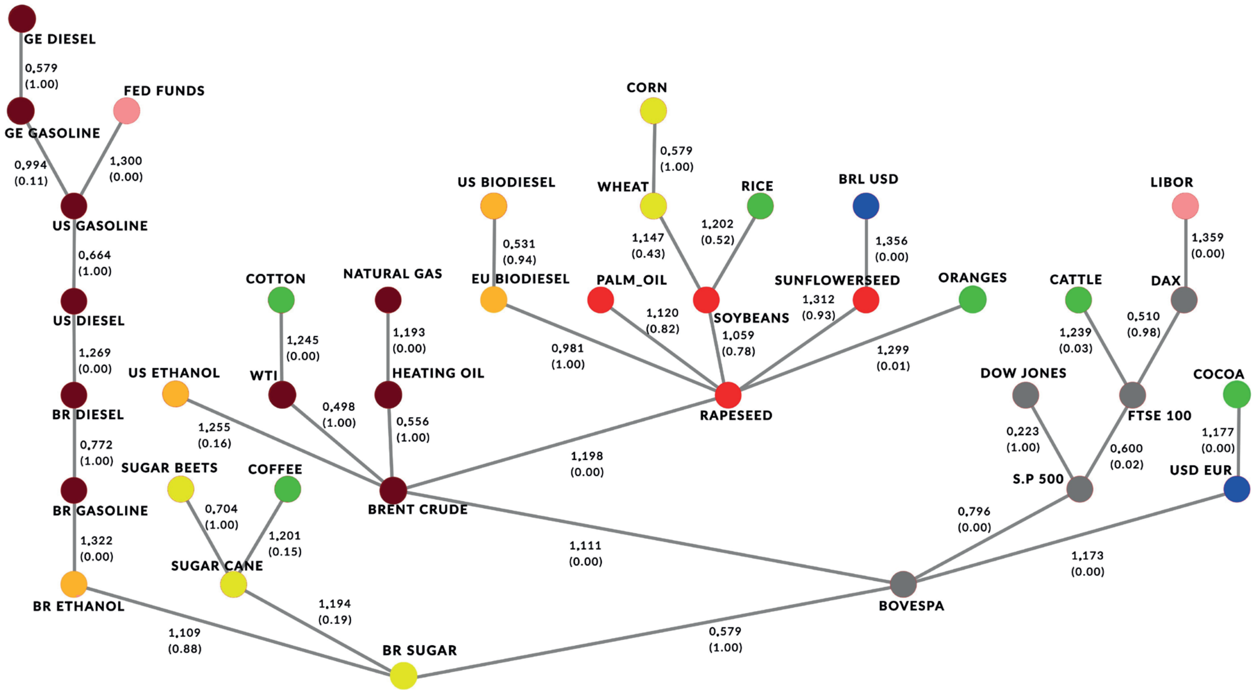

Figure 2. Minimum spanning tree – Entire period 2003–2020

Colour-code: orange – biofuels; yellow – bioethanol feedstock; red – biodiesel feedstock; green – food commodities; dark red – fossil fuel; grey – stock indices; pink – interest rates; blue – exchange rates

The numbers in parenthesis represent a percentage of appearance of particular link in 1 000 bootstrapped replications

Source: Own calculations based on Thomson Reuters Eikon (2020), Bloomberg Datastream (2020), U.S. Energy Information Administration (2020), ANP (2020), Federal Reserve Bank of St. Louis (2020), CEPEA (2020)

described by Sieczka and Hołyst (2009). The commodities that are in a cluster together either belong to the same sector or are interconnected in a similar way.

We were able to distinguish among five main clusters. The first one consists of the stock indexes that were further present in some form in all of the MSTs presented here. From there, we observed the connection provided by the Brazilian stock market index, Bovespa, which is not very meaningful on its own, on the basis of the bootstrapped b_{ij} value, but provides a connection to other clusters.

Although the colour code for related commodities and assets in general clearly indicates that similar assets are usually clustered together, a clear exception are interest rates and agricultural commodities not serving as a biofuel feedstock, which are spread all over the MST, with d_{ij} close to $\sqrt{2}$, indicating very low correlation, and with b_{ij} close to 0, indicating low stability of the particular connection. We followed up with MSTs for specific periods.

In Figure 3, we considered the period from November 2003 to August 2007. This period was an initial stage of a biofuel boom, with biofuel-supporting policies being promoted all over the globe. During this period, there was a significant increase in the production of biofuels connected with very strong expectations of future further large expansions of biofuel production driven by both government support policies and market forces. During this period, the refinery capacities and further infrastructure were in the process of expansion, generally lagging behind the increasing demand.

The strongest connection in the MST for this period is the one between American and European biodiesel. The important thing to notice here is the quite weak but very stable connection to rapeseed as the main feedstock. The second-lowest pair is known to us from the previous MST – the Dow Jones and S&P 500 (0.294) with $b = 1$. Furthermore, all of the stock indexes form a very connected cluster; note the connection between the FTSE 100 and DAX, along with the connection between the DAX and S&P 500. A very stable pair across all of the periods was that of sugar cane and sugar beets, with the distance of 0.321, which is understandable given that the sugar from sugar beets and sugar cane is nearly identical (Kramer 2016).

Another common pair is that of Brent crude oil and WTI (0.424, with $b = 1$), which is not surprising be-

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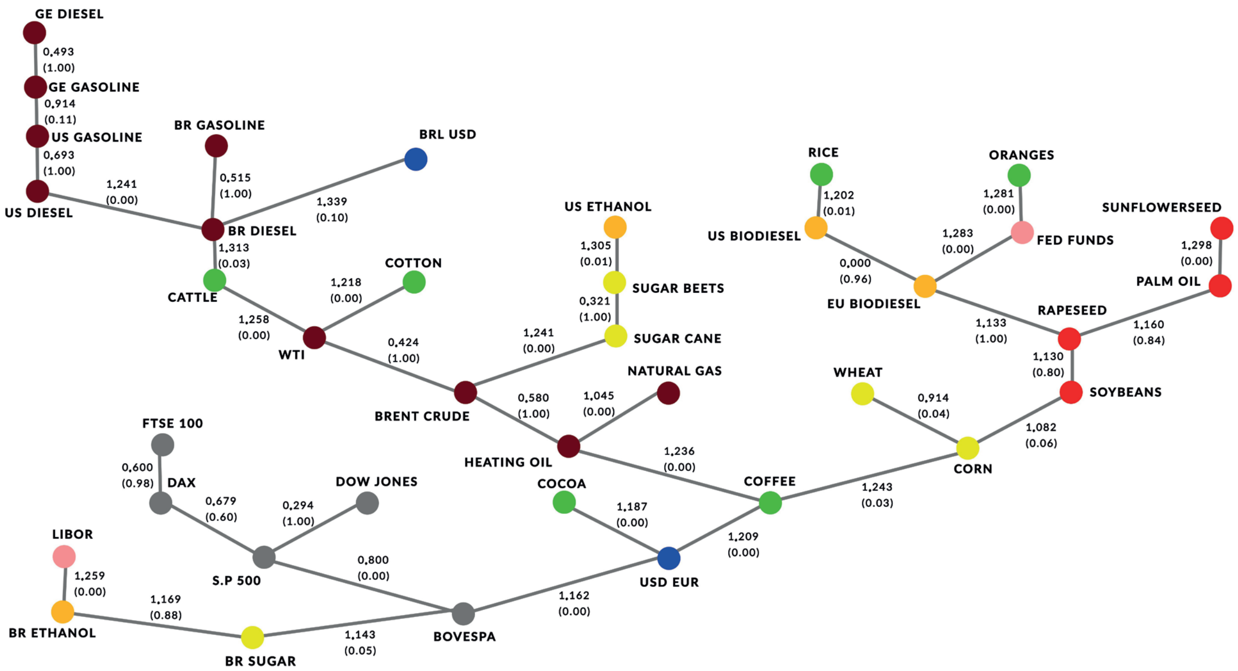

Figure 3. Minimum spanning tree – Period I

Colour-code: orange – biofuels; yellow – bioethanol feedstock; red – biodiesel feedstock; green – food commodities; dark red – fossil fuel; grey – stock indices; pink – interest rates; blue – exchange rates
The numbers in parenthesis represent a percentage of appearance of particular link in 1 000 bootstrapped replications
Source: Own calculations based on Thomson Reuters Eikon (2020), Bloomberg Datastream (2020), U.S. Energy Information Administration (2020), ANP (2020), Federal Reserve Bank of St. Louis (2020), CEPEA (2020)

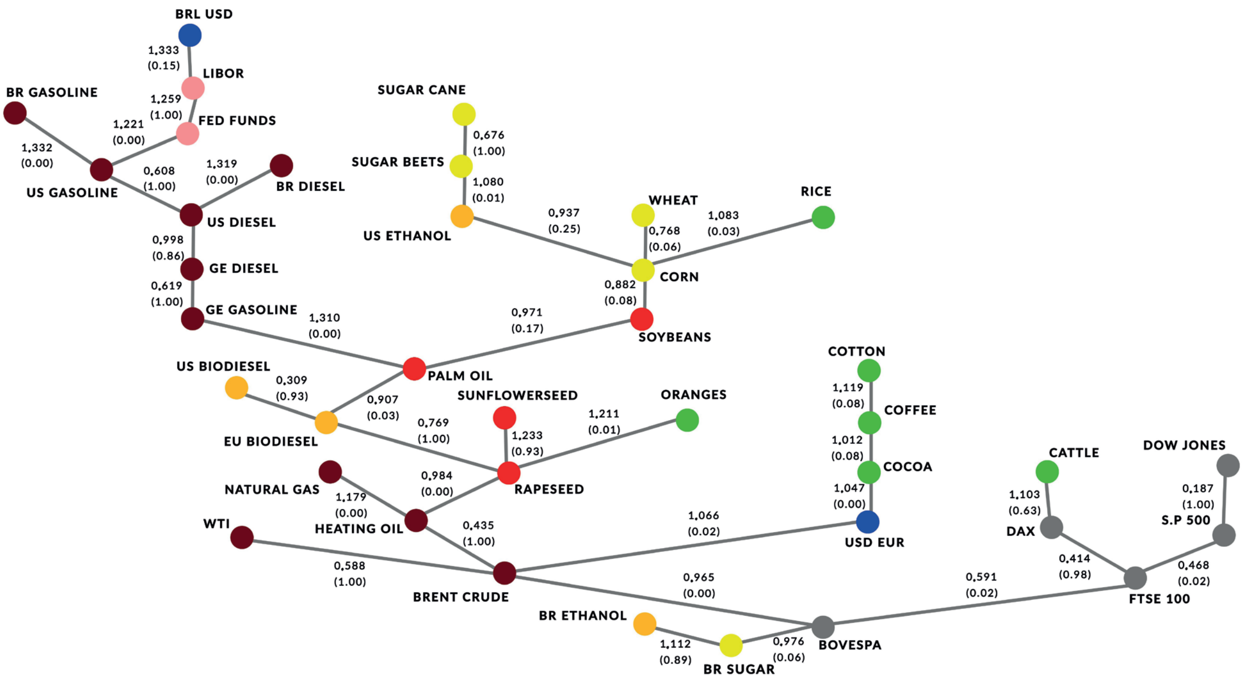

Figure 4. Minimum spanning tree – Period II

Colour-code: orange – biofuels; yellow – bioethanol feedstock; red – biodiesel feedstock; green – food commodities; dark red – fossil fuel; grey – stock indices; pink – interest rates; blue – exchange rates
The numbers in parenthesis represent a percentage of appearance of particular link in 1 000 bootstrapped replications
Source: Own calculations based on Thomson Reuters Eikon (2020), Bloomberg Datastream (2020), U.S. Energy Information Administration (2020), ANP (2020), Federal Reserve Bank of St. Louis (2020), CEPEA (2020)

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cause they are both seen as the global benchmark references for crude oil prices. They are followed by the connection of Brent crude oil with heating oil (0.580, with b = 1). However, there is no established connection between heating oil and WTI, which would normally be there, but because it would create a loop, the algorithm minimising the number of links did not include it. Obvious but still very important connections were established between the gasolines and diesels – namely, German diesel and gasoline (0.493), US diesel and gasoline (0.693) and Brazilian diesel and gasoline (0.515). All of these relationships also were very stable in the bootstrapped cases. The process then continued to create the whole MST in Figure 3.

Figure 3 shows three clusters – that of fossil fuels connected to crude oils and heating oil, the financial assets, such as stock indexes, and biofuels that are connected to their feedstock. A very interesting link seen throughout the whole period is that of Brazilian ethanol and sugar. This link is so stable mainly because Brazil's market was already well established since the production of biofuels begun in the 1970s. Another reason for that stability is the government's interventions and subsidisation (Koizumi 2003), as well as being related to the monopoly situation with Brazil's Petrobras, which is seen as the only important market player for fuels. Also, biodiesel is already well connected to its feedstock, whereas US ethanol is not yet connected to its major feedstock, corn.

The next two periods of biofuel development are captured in Figure 4 (September 2007 to October 2011) and Figure 5 (November 2011 to December 2015).

The last period after 2016 (Figure 6) can be characterised as a return to a stable proportional development of both biofuels and agriculture in a stabilised policy environment. If we look at the Food Price Index, which was also included in the previous part, the prices of commodities and assets in this period seem to be without any increasing or decreasing trend and are not very volatile. A major feature of this period of mature biofuel markets is a close connection of both US and Brazilian ethanol, connected through the US financial markets. This alignment of the US and Brazilian ethanol prices also means that US agricultural markets recovered from a period of ethanol production being the main driving force for US corn production.

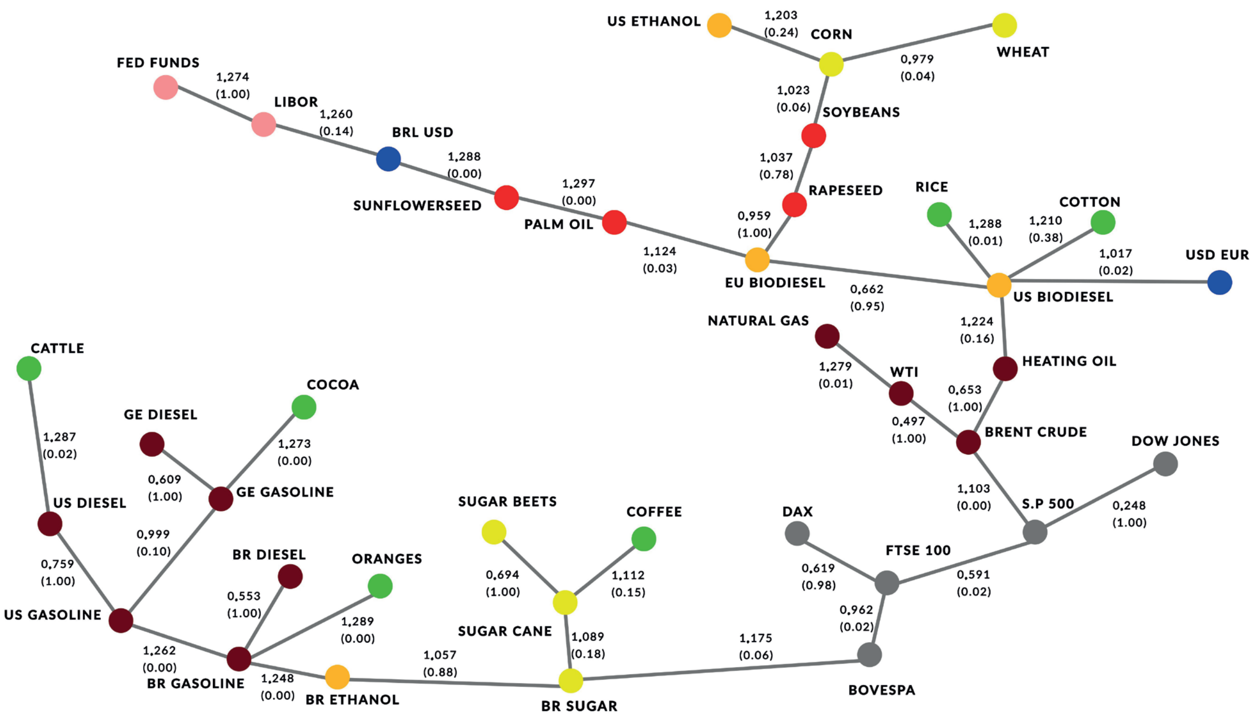

Figure 5. Minimum spanning tree – Period III

Colour-code: orange – biofuels; yellow – bioethanol feedstock; red – biodiesel feedstock; green – food commodities; dark red – fossil fuel; grey – stock indices; pink – interest rates; blue – exchange rates
The numbers in parenthesis represent a percentage of appearance of particular link in 1 000 bootstrapped replications
Source: Own calculations based on Thomson Reuters Eikon (2020), Bloomberg Datastream (2020), U.S. Energy Information Administration (2020), ANP (2020), Federal Reserve Bank of St. Louis (2020), CEPEA (2020)

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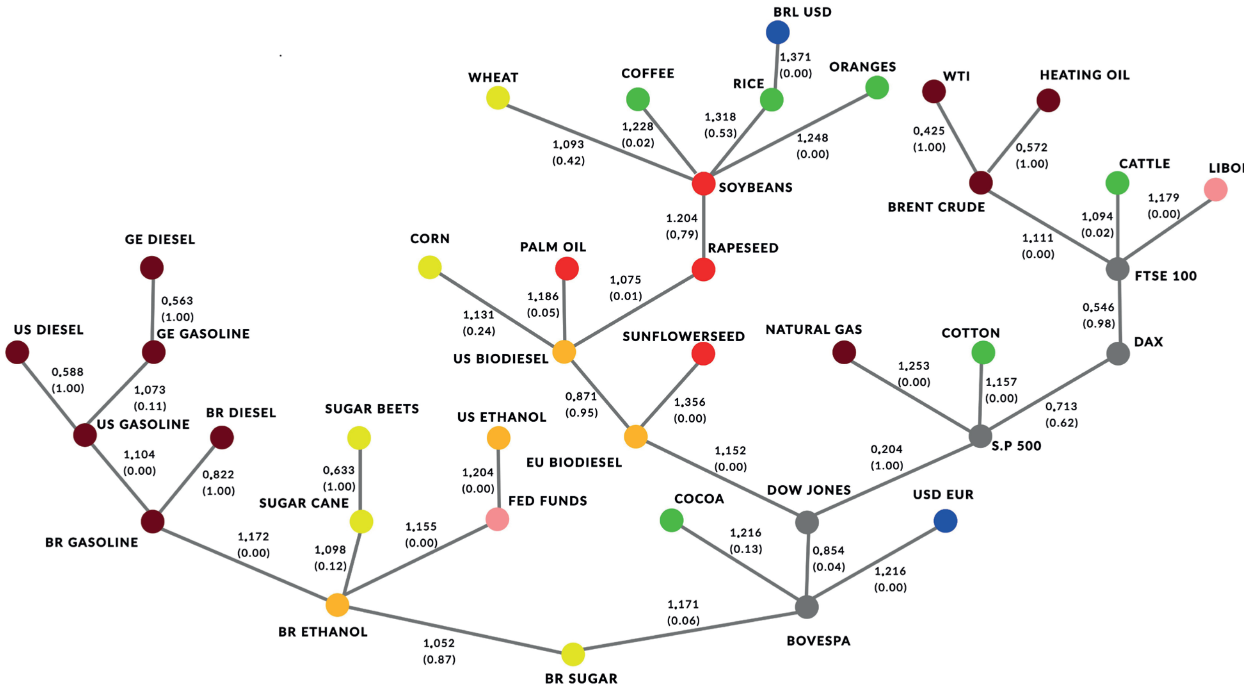

Figure 6. Minimum spanning tree – Period IV

Colour-code: orange – biofuels; yellow – bioethanol feedstock; red – biodiesel feedstock; green – food commodities; dark red – fossil fuel; grey – stock indices; pink – interest rates; blue – exchange rates
The numbers in parenthesis represent a percentage of appearance of particular link in 1 000 bootstrapped replications
Source: Own calculations based on Thomson Reuters Eikon (2020), Bloomberg Datastream (2020), U.S. Energy Information Administration (2020), ANP (2020), Federal Reserve Bank of St. Louis (2020), CEPEA (2020)

Even after a relatively long period of development of US ethanol and both US and European Union biodiesel, Brazilian ethanol and commodities and assets closely related to them still kept their central position of the most developed and best integrated biofuel system. Brazilian ethanol connects US ethanol to a compact cluster of vehicle fuels and through the Bovespa financial index connects with other major financial indexes to the oil branch of the fossil fuel system.

CONCLUSION

Our comparison of MSTs over distinct periods shows an interesting change in the structure of the price interconnection of biofuels and related assets and commodities, along with the global development of biofuels and related policies. During the initial period of biofuel development, it was clear that all fossil fuels considered in our analysis stood apart as a clearly defined and closely interconnected group without a strong interaction with biofuels, so it was a time when agricultural commodities and fossil fuels were still much less connected.

During the 18 years covered in our analysis, we observed a clear erosion of the initial firm cluster of fossil fuels. Although the institutional decoupling of the prices of natural gas and oil, driven by industrial organisation policies rather than biofuel policies, was a major force in driving natural gas away from the WTI/Brent crude/heating oil cluster, the separation of highly processed vehicle fuel prices from the prices of non-vehicle raw oils was closely connected with the advances of biofuels. This finding is particularly strong for ethanol, which became closely aligned with vehicle fuels, mainly because of mandatory blending requirement policies. For biodiesel, the technological properties different from those of ethanol, leading to different blending policies meant that it was not as close to fossil vehicle fuels as was ethanol, but biodiesel was still a part of a large vehicle fuel-related cluster.

An important regularity over the whole investigated period was a close and stable direct connection between the European Union and US biodiesel together with their close connection with their feedstock. In the same way, we have documented a strong and stable direct connection between Brazilian ethanol and its sugar cane feedstock, which was represented by sugar. However, US ethanol behaved differently from other biofuels. Figures 2–6 seem to indicate that a close connection

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of US ethanol and its major feedstock, corn, was not a natural stable situation. This close connection of ethanol and corn occurred only during the period of food crises and during the subsequent period of stagnation for biofuels. Both during the initial period of market build-up for biofuels and during a more recent period of market stabilisation for biofuels, the US ethanol price was related more to fossil fuel prices than to corn prices.

The positive connection between the prices of fossil fuels and agricultural commodities was a common result of both our research and that seen in other recent literature covering a comparably long period (Pal and Mitra 2020; Tiwari et al. 2021). However, although these other investigators conclude that this co-movement is due to ethanol mandates, without explicitly considering the development of prices of ethanol and other biofuels, we are much more explicit in directly covering all relevant prices, including the prices of biofuels.

In addition to fossil fuels and biofuels being closely related commodities, our results included two other big groups of prices that used to be related to biofuels in some of the previous literature. For the food commodities outside of biofuel feedstock groups, our results clearly showed that in no period were they important for price transmission in a large system of biofuels and fuels. However, for financial assets, the situation was different. Although particular financial assets served as important connectors for the price transmission of biofuels and fuels in different periods, they also became more systemically important for the whole system of biofuels and fuels as a major connector between vehicle fuels and raw oil clusters, which had become separated over time because of the growing importance of biofuels in the fuel system.

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